

**SUBJECT-INDEPENDENT
ERP-BASED BRAIN-COMPUTER
INTERFACE USING ADAPTIVE
AND ENSEMBLE LEARNING**

by

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Abstract

The breakthrough of deep learning in recent years opens up a wide range of applications, mostly from computer vision to brain-computer interface (BCI), which is the research topic of this thesis. In our study, we propose a unified framework of the subject-independent event-related potential (ERP) based BCI. In other words, we attempt to overcome a major challenge of discrepancies in ERP patterns across different subjects by employing a deep learning technique, accompanied with different strategies of bagging-stacking ensemble, dynamic stopping, and adaptive incremental learning. The main contributions of this thesis are summarised as follows:

(1) Employ the subject-adversarial neural network (SANN) to learn the optimal representation for the original preprocessed ERP features. This network serves as a feature encoder which attempts to find a better feature space that is subject-independent for the testing procedure.

(2) Employ three machine learning algorithm as base learners: support vector machine (SVM), Fisher’s discriminant analysis (FDA), and fully-connected feedforward neural network (NN). The soft scores of these base learners serves as inputs for the ensemble strategy which is comprised of two widely-used techniques: bagging and stacking. The goal of the whole ensemble strategy is to perform the binary classification problem of ERP trials with lower generalisation error and higher accuracy.

(3) Employ two post-processing tasks for the P300-Speller (P3S) to enhance the information transfer rate, namely dynamic stopping (DS), and adaptive (or incremental) learning (AL). DS is performed to let the system produce the subject’s output whenever the algorithm is sufficiently confident about its decision, while AL is used to reinforce the existing classifier by analytically integrating newly-classified samples into the classifier’s decision function in real-time.

The research of the thesis is motivated by the strong representative characteristics of ERP features in EEG signal. The distinctive properties of ERP, especially P300 component in this thesis, and its variability across multiple subjects, can be well-exploited by the high complexity and employment of deep adversarial neural network framework. The robust representation features output of this network are served as learning features for the subsequent step of ensemble learning by multiple machine learning algorithms. Finally, some post-processing and enhancement methods specifically proprietary to this thesis such as dynamic stopping and incremental learning are applied to yield an additional boost in our performance.

Certificate of Original Authorship

I, Anh Kha Vo, declare that this thesis, is submitted in fulfillment of the requirements for the award of the degree of Doctor of Philosophy, in the School of Electrical and Data Engineering, Faculty of Engineering and Information Technology, at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference of acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature:

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Signature removed prior to publication.

Anh Kha Vo

Date: 20th, October 2018.

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List of Publications

The publications of the author during his PhD study are listed as follow.

Journal Papers:

[1] **Kha Vo**, Thuy Pham, Diep Nguyen, Kha Ha & Eryk Dutkiewicz, “Subject-Independent ERP-based Brain-Computer Interfaces”, IEEE Transactions on Neural System and Rehabilitation Engineering, Vol.26, No.4, pp. 1-10, **2018**. (related to Chapter 3, 5, 6)

[2] **Kha Vo**, Rifai Chai, Kha Ha & Eryk Dutkiewicz, “Subject-Adversarial Neural Network for ERP Classification”, IEEE Transactions on Biomedical Engineering, **2018** (Under Review/Submission) (related to Chapter 4).

[3] **Kha Vo**, Kha Ha & Michael Blumenstein, “Extraction of Dynamic Trajectory on Multi-Stroke Static Handwriting Images Using Loop Analysis and Skeletal Graph Model”, IEEE REV Journal on Electronics and Communications, Vol. 6, No. 1-2, **2016**.

Conference Papers:

[4] **Kha Vo** & Eryk Dutkiewicz, “Optimal Length-Constrained Segmentation and Subject-Adaptive Learning for Real-time Arrhythmia Detection”, ACM/IEEE Conference on Connected Health: Applications, Systems, and Engineering Technologies (CHASE), Big Data for Health Workshop (BIG-DATA4HEALTH) , Washington DC, USA, **2018**. (related to Chapter 6)

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- [5] **Kha Vo**, Diep Nguyen, Kha Ha & Eryk Dutkiewicz, “Subject-Independent P300 BCI using Ensemble Classifier, Dynamic Stopping and Adaptive Learning”, IEEE Global Communications Conference (GLOBECOM), Singapore, **2017**. (related to Chapter 3, 6)
- [6] **Kha Vo**, Diep Nguyen, Kha Ha & Eryk Dutkiewicz, “Real-Time Analysis on Ensemble SVM Scores to Reduce P300-Speller Intensification Time”, 39th International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jeju Island, Korea, **2017**. (related to Chapter 5)
- [7] **Kha Vo**, Diep Nguyen, Kha Ha & Eryk Dutkiewicz, “Dynamic Stopping Using eSVM Scores Analysis for Event-Related Potential Brain-Computer Interfaces”, 11th International Symposium on Medical Information and Communication Technology (ISMICT), Lisbon, Portugal, **2017**. (related to Chapter 6)
- [8] **Kha Vo** & Kha Ha, “Extraction of dynamic features from static handwritten image and recognition using Hidden Markov model”, International Symposium on Electrical and Electronics Engineering (ISEE), Saigon, Vietnam, **2015**.
- [9] Kha Ha, **Kha Vo** & H. Dinh, “Brainwave-Controlled Applications with the Emotiv EPOC Using Support Vector Machine”, 4th International Conference on Information Technology, Computer, And Electrical Engineering (ICI-TACEE), Semarang, Indonesia, **2016**. (related to Chapter 3)
- [10] Kha Ha & **Kha Vo**, “Real-Time Brainwave-Controlled Interface Using P300 Component in EEG Signal Processing”, 12th IEEE-RIVF International Conference on Computing and Communication Technologies, Hanoi, Vietnam, **2016**. (related to Chapter 3)

Abbreviations

Ag Silver

AgCl Silver-chloride

AL Adaptive Learning

ALI Adversarially Learned Inference

ALS Amyotrophic Lateral Schlerosis

ANN Artificial Neural Network

Au Gold

Bagging Bootstrap Aggregating

BCI Brain-Computer Interface

BLDA Bayesian Linear Discriminant Analysis

BMI Brain-Machine Interface

CNN Convolutional Neural Network

CNS Central Nervous System

CNV Contingent Negative Variation

CT Computed Tomography

DANN Domain Adversarial Neural Network

DCGANN Deep Convolutional Generative Adversarial Neural Network

deoxy-Hb Deoxy-hemoglobin

DNI Direct Neural Interface

DNN Deep Neural Network

DS Dynamic Stopping

ECoG Electrocorticography

EEG Electroencephalography

ERD Event-Related Desynchronisation

ERP Event-Related Potential

ERS Event-Related Synchronisation

FDA Fisher's Discriminant Analysis

FES Functional Electrical Stimulator

fMRI Functional Magnetic Resonance Imaging

FN False Negative

fNIRS Functional Near Infrared Spectroscopy

FP False Positive

GANN Generative Adversarial Neural Network

GPU Graphics Processing Units

ISVM Incremental Support Vector Machine

KKT Karush-Kuhn Tucker

KL Kullback-Leibler

LDA Linear Discriminant Analysis

LFP Local Field Potential

LgR Logistic Regression

LR Linear Regression

MLP Multilayer Perceptrons

MMI Mind-Machine Interface

MRI Magnetic Resonance Imaging

N1 Negative 100ms

N100 Negative 100ms

N2 Negative 200ms

N200 Negative 200ms

NN Neural Network

OOF Out-of-fold

oxy-Hb Oxy-hemoglobin

P1 Positive 100ms

P100 Positive 100ms

P2 Positive 200ms

P200 Positive 200ms

P3 Positive 300ms

P300 Positive 300ms

P3S P300-Speller

PCA Principle Component Analysis

PET Positron Emission Tomography

PPT Peak-to-Peak Thresholding

Pt Platinum

ReLU Rectified Linear Unit

SANN Subject Adversarial Neural Network

SCI Spinal Cord Injury

SCP Slow Cortical Potential

SGD Stochastic Gradient Descent

SMR Sensorimotor Rhythm

Sn Tin

SNR Signal-to-Noise Ratio

SPECT Single Photon Emission Computed Tomography

SQUID Superconducting Quantum Interference Device

SSVEP Steady-State Evoked Potential

SVM Support Vector Machine

TN True Negative

TP True Positive

t-SNE t-distributed Stochastic Neighbor Embedding

TTD Thought Translation Device

UCLA University of California, Los Angeles

VEP Visually Evoked Potential

WPPT Windowed Peak-to-Peak Thresholding

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